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A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models

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ABSTRACT

Building energy use prediction plays an important role in building energy management and conservation as it can help us to evaluate building energy efficiency, conduct building commissioning, and detect and diagnose building system faults. Building energy prediction can be broadly classified into engineering, Artificial Intelligence (AI) based, and hybrid approaches. While engineering and hybrid approaches use thermodynamic equations to estimate energy use, the AI-based approach uses historical data to predict future energy use under constraints. Owing to the ease of use and adaptability to seek optimal solutions in a rapid manner, the AI-based approach has gained popularity in recent years. For this reason and to discuss recent developments in the AI-based approaches for building energy use prediction, this paper conducts an in-depth review of single AI-based methods such as multiple linear regression, artificial neural networks, and support vector regression, and ensemble prediction method that, by combining multiple single AI-based prediction models improves the prediction accuracy manifold. This paper elaborates the principles, applications, advantages and limitations of these AI-based prediction methods and concludes with a discussion on the future directions of the research on AI-based methods for building energy use prediction.

1. Introduction

Population growth and economic development in many ways propelled energy and material consumption to a greater degree that threatens the very existence of our Earth. Globally, buildings account for nearly 30% of global energy usage [1]. Needless to say, any effort toward decreasing building energy use considerably reduces the reliance on global energy. With a significantly large stock of buildings still put to use by, in some cases, over-extending their useful life by retrofitting through material upgrades, the importance of building energy efficiency cannot be understated. For one, the insulation requirements for most of the buildings built in the mid-twentieth century lack insulation requirements that may have prevented heat loss or gain. Besides, the inaccuracy or lack of calibrated sensors to control energy and lighting pose a continuous struggle to effectively track, control, and reduce energy use. Thus, with existing buildings posing a threat to overall energy efficiency, recent decades have seen an increase in research activities in the field of energy use prediction particularly using Artificial Intelligence (AI) techniques. This necessity has attracted many researchers attempting to predict energy use in a rapid manner. Among others, energy use prediction contributes to effective building energy management and conservation, energy systems commissioning through detecting system faults, and building energy control and operation [2].

Researchers have developed various simulation tools to predict building energy use since the early 1990s. These tools can be further classified as engineering method, AI-based method, and hybrid method [3]. The engineering method estimates energy use by using thermo-

Abbreviations: ANFIS, Adaptive Network-based Fuzzy Inference System; ANN, Artificial Neural Network; ARIMA, Autoregressive Integrated Moving Average; ARMAX, Autoregressive Moving Average with Exogenous inputs; BC, Bayesian Combination; BNB, Bernoulli Naïve Bayes; BSS, Blind Source Separation; BT, Boosting Tree; CART, Classification and Regression Tree; CHAID, CHi-squared Automatic Interaction Detection; CR, Case-based Reasoning; DHC, Double-layer Hierarchical Combining; DS, Dynamic Selection; DSR, Dempster-Shafer Regression; DT, Decision Tree; EN, Ensemble Node; FFNN, Feed Forward Neural Network;; GA, Genetic Algorithm; GA-ANFIS, Genetic Algorithm - Adaptive Network-based Fuzzy Inference System;; GENLIN, Generalized Linear model; kNN, k-Nearest Neighbors;; LEW, Least-squares Estimation-based Weighting; MA, Median-based Averaging; MAPE, Mean Absolute Percentage Error; MARS, Multivariate Adaptive Regression Splines;; MLP, Multi-Layer Perceptron; MNB, Multinomial Naïve Bayes; MS, Multi Staging; MV, Majority Voting; PCA, Principal Component Analysis; PNN, Probabilistic Neural Network; RBFNN, Radial Basis Functions Neural Networks; RC, Resistor–Capacitor;; RF, Random forest; RIPPER, Repeated Incremental Pruning to Produce Error Reduction; RMS, Reverse Multi Staging; RNN, Recurrent Neural Network;; SA, Simple Average; SARIMA, Seasonal Autoregressive Integrated Moving Average; SASOM, Structure Adaptive Self-Organizing Map; SOM, Self-organizing Map; SVM, Support Vector Machine; SVR, Support Vector Regression; WA, Weighted Average; WPA, Weighted Probability Averaging; WV, Weighted voting

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dynamic equations to represent the physical behavior of systems and their interactions with the environment to estimate energy use, i.e., energy consumption of individual building component or the entire building [4]. This method is referred to as the 'white-box' as the inner logic is known. Different from engineering approach, the AI-based method is referred to as the 'black-box' because it predicts energy use without knowing the internal relationship of the building and its individual components. The hybrid method, also known as the 'grey-box', integrates both white-box and black-box methods for the purpose of eliminating the limitations inherent in each method. Both white-box and grey-box methods require detailed building information to simulate the inner relations to estimate energy use and, therefore, are time-consuming and require tedious expert work for model development. For the study of existing buildings and their energy use, the use of these two methods becomes tedious as, if not impossible, it may be difficult to accurately gather specifications of building envelope and mechanical systems thus thwarting the widespread use of these methods for existing building stock. Whereas a detailed review of tools for building energy use prediction including the white-box, black-box, and grey-box methods is available in [3], this paper presents an in-depth review of the state-of-the-art AI-based methods for building energy prediction. Two prediction methods are studied and compared; they are single prediction methods that utilize one learning algorithm and ensemble prediction methods which integrate some of the single prediction methods to improve accuracy of prediction.

AI-based prediction method predicts building energy use according to its correlated variables such as environmental conditions, building characteristics, and occupancy status. Due to its prediction performance, AI-based methods have been widely applied in the domain of building energy use prediction. Previous studies have compared the AI-based methods with other prediction methods for building energy use. To give examples: Neto and Fiorelli [5] compared Artificial Neural Network (ANN) with EnergyPlus [6], a whole building energy estimation software, for predicting building energy use; Turhan et al. [7] compared Back Propagation Neural Network (BPNN) with KEP-IYTE-ESS [8], another energy simulation tool, for predicting the heating load of residential buildings; and more. These studies demonstrated the AI-based approaches, with advantages such as model simplicity, calculation speed, and learning capability when compared with the engineering and hybrid methods, is the most suitable method in energy use prediction of existing building stock. Because of their simple model structure and convenient data collection necessities, AI model development is rapid. To elaborate, the energy simulation engines such as EnergyPlus, although they can model complex systems, are comparatively slower than AI-based approaches owing to the sequential operations of the software structure, e.g., the space temperature is updated hourly using feedback from HVAC module. Furthermore, using time series data, AI-based models can be employed to predict future behavior of energy use whereas energy modeling software, as forward classical approach, offer energy estimation on a 15-min, hourly, monthly, or annual basis for the known structure. This leads to one of the significant advantages of AI-based models, in that, they require a small number of parameters that adequately represent the performance of the building, as a system when compared to a whole building energy simulation algorithms which require known structure and known parameters as they are subjected to input variables for estimation.

This paper provides a detailed literature review on the recent developments of AI-based building energy use prediction. The paper first investigates the current research trends of AI-based building energy use prediction. More specifically, this paper provides insight into a more recently applied approach for AI-based building energy prediction – the ensemble learning, which combines multiple AI-based models to improve prediction accuracy. After reviewing various AI-based models, this paper offers a detailed comparison between the conventional single prediction (i.e., using one AI-based model) and ensemble prediction models (i.e., using multiple AI-based models). Furthermore, using detailed discussion including principles, applications, and comparisons, this review paper offers the necessary constructs for successful ensemble model implementation. In a nutshell, this paper paves the way for greater understanding of the use of ensemble models for the prediction of building energy use.

The paper is organized as follows: Section 2 provides a review of current research trends of AI-based building energy use prediction. Section 3 discusses the principles, advantages, limitations, of different AI-based prediction models. Section 4 compares AI-based single and ensemble prediction methods and discusses the advantages, disadvantages, and future directions of AI-based building energy use prediction. Finally, conclusions are discussed in Section 5.

2. Current trends: AI-based building energy use prediction

To aid readers' understanding of current research trends of AI-based building energy use prediction as well as to reveal some of the common features used in research studies, we reviewed related journal articles published in recent six years (2011–2016). A total number of 35 representative journal articles were identified to comprehend the current research status and trends of AI-based building energy use prediction. The selection criteria for narrowing recent work included the building types, prediction approaches, energy output types predicted, time scale of the prediction, and input data types used for prediction. Table 1 compares the recent work in the field of AI-based approaches for building energy prediction using the criteria discussed earlier. The current research trends of AI-based building energy use prediction based on the investigation results of each aspect are discussed in the following part of this section.

2.1. Building type

For AI-based prediction, a validation process is always needed to test the prediction performance of the proposed prediction model. Based on the literature review, different types of buildings were used as the testbed to validate the prediction performance of the proposed prediction model. According to the functional usage, the tested buildings may be classified into four categories, e.g., commercial, residential, educational and research, and other building types. As shown in Fig. 1, the literature review performed in this paper indicates that the AI-based prediction models were largely used for energy prediction of the educational and research, and commercial building types, i.e., 42% and 33% respectively. These building types are most preferred for researchers to apply their AI-based prediction models particularly due to data availability and, potentially, easier access to the available data. Notably, although the residential buildings account for the largest proportion of building energy use [42], there are limited studies related to the application of AI-based approaches to predict energy use. Perhaps, this is due to the difficulty in data collection for residential buildings has adequately slowed the use of AI-based energy use prediction. Compared to educational and research buildings, residential buildings, particularly the single-family houses, are short of sensors and meters to collect occupancy and energy data, which are essential for AI-based prediction models. Even for large residential buildings such as apartment buildings, where adequate sensors may be available, it is hard, if not impossible, for researchers to collect the required data owing to privacy issues.

2.2. Prediction method

Various AI-based energy prediction models were proposed in the reviewed articles. According to the model structure and the number of prediction models used, these models may be classified into two categories: single and ensemble prediction models. Our study results show that the single prediction method is widely used for AI-based